Extending Model-Based Diagnosis for Analog Thermodynamical Devices

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Abstract

The increasing complexity of process control applacations have posed difficult problems in fault detect ion, isolation, and recovery (FDIR). Deep knowledge-based approaches, such as model-based diagnosis, have offered some promise in addressins these problems. However, the difficulties of adapting these techniques to situations involving numerical reasoning and noise have limited the applicability of these techniques.

This paper describes an extension of classical]mctc.J-based diagnosis techniques[2] to deal with sparse data, noise, and complex non-invertible numerical models. These diagnosis techniques arc. being applied to the External Active Thermal Control System (EATCS) for Space St ation Freedom.,

1 Introduction

This paper describes an original approach to model-based diagnosis drive.n by application constraints. Due to the complexity of the Physical processes involved in EATCS, the model developed is a lumped parameter mode of the steady - state. behavior. The engineering effort required to build a dynamic, lumped parameter model would have been comparable to that of building a bigJ1-fidelity mode.t.

Whereas a dynamic model would integrate differential equations to predict tbc model response, a s[cacty-state model computes only the stable. model response for every change to the model inputs. Consequently, the intermediate value.s for the model variables cannot be trusted as representative of the model transit.nt behavior.

To keep the diagnosis tool domai n independent, wc use the component/connection paradigm for modeling as described in section 2. Each component is modeled in terms of *design parameters*, *variables* and *constraint equations* defined from variables and parameters. The model of the physical system is dc.rived from the interactions among constituent components modeled as component connections. The embedding of the physical system in an environment is modeled as interactions with external inputs and observable variables or *sensors*. Sect ion 3 illustrates this modeling framework with a simplified evaporator loop taken from the EATCS.

Given a mode.1 of a physical system, there arc. several classes of diagnoses base.cl cm the level of (diagnostic conclusions desired and which sensors and external inputs arc believed in. Section 4 discusses the possible diagnostic conclusions in terms of the data believed in and the diagnostic hypotheses made.

Section 5 discusses the underlying diagnosis machinery: the adaptat ion of const rai nt suspension to coat inuous, steady - state models similar to [3] for analog models. For digital domains formalized in logic, constraint suspension is complete in that al I of the consistent states can be found for any suspended constraint. In continuous domains, the adaptat ion of const rai nt suspension presented here c requires severe restrictions for it to be complete.

Section 6 describes the overall diagnostic process from anomaly detect ion to hypothesis formation and validat ion. Finally sec. 7 describes the implementation status and sec 8 concludes this paper.

2 Modeling

The model of each system component is defined by a set of constraints. Each coast raint e corresponds to one or nmrc analytical equations. The domain of a constraint, $D(c)$, is the set of component parameters and variables used in tbc equations of the. constraint c.

Given a component c, the set of all parameters $P(c)$ of that con ponent represents the physical characterist its" of c. The set of values of al 1 component variables, *V(c)*, represents the component state of c at a given instant. For example, the diameter of a venturi component is a design parameter whereas the flow rate through the venturi is a stat c variable. A variable of a component is *sensed* when there is a physical sensor providing external observat ions of that variable. For a system model M, $C(M)$ represents the set of comp onents of that model, $E(M)$ represents the set of constraints of C(M), and $S(M)$ is the set of sensed component variables, thus $S(M) \subseteq \bigcup_{c \in C(M)} V(c)$. $I(M)$ represents the set of external inputs to the model.

The constraint model of a system M is a graph, $M = (\mathcal{V}, \mathcal{E})$, whose vertices are

$$\mathcal{V} = E(M) \bigcup \left(\bigcup_{c \in C(M)} V(c) \bigcup P(c) \right) \bigcup I(M)$$

and edges arc defined by:

$$\mathcal{E} = \{c - x \mid c \in E(M), x \in (\mathcal{V} - E(M)) \bigcap D(c)\}$$

That is, V is the set of all constraints, external inputs anti the variables and parameters of each component of the model. $\mathcal{E}$ is [II(set of edges constructed from the dependencies between the equations corresponding to each constraint and the graph vertices appearing in those equations.

For a constraint c and $D(c) = \{x_1, \ldots x_n\}$, the constraint is described as an equation:

$$(c) \qquad f(x_1, x_2, \ldots, x_n) = 0$$

where f is the function characterizing c. An model constraint c is invertible if there exists n *projection functions*, f_{x_i} for each x_i $(1 \leq i \leq n)$ such that the model constraint c is equivalent to:[1]

$$f(x_1, x_2, \ldots, x_n) = f_{x_i}(x_1, \ldots, \widehat{x_i}, \ldots x_n) - x_i = 0.$$

The invertability of a model constraint affects which techniques can be used to rc.solve. a set of k constraints with n unknown variables or parameters. When model constraints are invertible and their derivatives are also invertible, then a solution can easily be found. When a model constraint has irreversible projection functions, it is no longer possible to invert a component constraint, instead the constraint has to be relaxed by searching for a set of possible values for the unknown variables or parameters.

'1'bus, one. of the requirements for constraint suspension for diagnosis is that model equations be either invertible or suitable for relaxat ion methods: cent i nuit y, differentiabilit y of the model function as well as that of all the partial derivatives of its projection functions. This lasi require.nlc.nt is there to guarantee that the mode.t functions are wc]] behaved. Monotonicity is not necessary for relaxation as long as every local minima and maxima of each projection function f_{x_i} can be analytically determined or numeric.al]y computed (e.g., by resolving $df_{x_i}/dx = 0$.)

Another source of mode.ting complexity stems from feedback. In simulation, feedback implies the need for relaxation methods to find a stable. solution to a feedback loop. In diagnosis, feedback can affect the constraint suspension process when 1) k-consistency methods arc used and 2) k is large enough to include al 1 of the coast raints of a feedback loop. la this case, feedback impacts constraint relaxation. Secondly, feedback affects the diagnostic interpretation process where the results of constraint suspension arc analyzed to conclude on the orig in of the anomalies.

3 EATCS evaporator model

Figure 1 shows a schematic diagram of a simplified evaporator model. '1 his model omits pipe.s and valve.s. However,

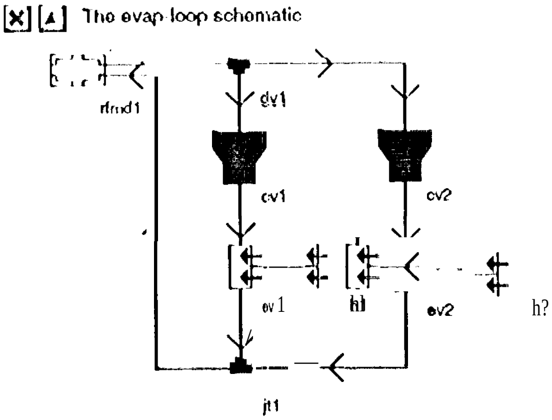

Figure 1: EATCS evaporator module

it retains important characteristics that make it a challenging diagnosis task. The model constraints corresponding to the hydraulic behavior of the evaporator are shown in Fig. 2. For brevity, the thermal interactions of this model have been omitted in this paper. None.thclcss, the model presented includes a passive. feedback loop combined with non-invertible model constraints.

Referring to Figure 1, the function of the Rotary Fluid Management Device (RFMD) is to supply saturated ammonia to the evaporator loop at a pressure that is dependent cm the set point pressure of the EATCS, the speed of the. RFMD, and the overall flow to the evaporator loop. The evaporator loop contains parallel branches, each containing, a cavitating venturi anti an evaporator. The cavitating venturis regulate the flow of ammonia to each evaporator as a function of the inlet pressure and ammonia saturation pressure, as long as cavitating behavior is achieved. The design flow rate of each Cavitating venturi is fixed by tile. design pressures and by the diameter of the venturi throat This flow rate. is determined such that the. evaporator can absorb its design heat load and still maintain a two-phase mixture at the evaporator outlet. Because this guarantees saturation conditions at the outlet, the temperature will be approximately the same around the loop.

The passive feedback loop occurs between the RFMD and the venturi/evaporator branches. Due to the passive flow-restricting behavior of the cavitating venturi, a change in evaporator loop inlet pressure can lead to changes in all cavitating venturi flows which then cause a global change in the evaporator loop flow, resulting in a further (but offsetting) change in the inlet loop pressure. Since there is no direct method to compute the new equilibrium point, several iterations are necessary to converge to a solution.

The presence of feedback signals the. need for relaxation to resolve the set crf model constraints since there arc no guarantees of a closed form solution avai lable for an arbitrary feedback model. During simulation for example., the nesting of feedback loops can have dire computational consequences: the simultaneous relaxation of multiple, interacting feedback loops can lead to oscillations.[2] In the EATCS evaporator, such oscillations can occur when a new flow/pressure point is tried

[1] The notation: $(x_1, \ldots, \widehat{x_i}, \ldots x_n)$ represents the n - 1 tuple derived from the n tuple $(x_1, \ldots x_i, \ldots x_n)$ by removing x_i. That is:

$$(x_1, \ldots, \widehat{x_i}, \ldots x_n) = \begin{cases} (x_2, \ldots, x_n) & \text{if } i = 1 \\ (x_1, \ldots, x_{i-1}, x_{i+1}, \ldots x_n) & \text{if } 1 < i < n \\ (x_1, \ldots, x_{n-1}) & \text{if } i = n \end{cases}$$

[2] This was a problem of aa earlier rule-based EATCS model which

as a solution lo the flow split among the evaporator branches while the RI'MD I' I oduces the inverse pressure/flow point.

The thermal constraints have been left out of this model. They descr ibe the heat-traasfcr from the heat sources (e.g., crew cabin) to the ammonia. Some of the constraints in Fig. ?. arc non-invertible and are shown with arrows.

For example ΛPrfmd as a function of Speed, Tpitot, and Flow is:

$$\Lambda P\mathrm{rfmd} \;=\; \rho\,\mathrm{Speed}^2 \times \mathrm{index}\left(\frac{\mathrm{Flow}}{\rho\,\mathrm{Speed}\,\phi^?}\right)$$

where ρ is the density of ammonia at temperature Tpitot and index is a non-inveitible function.

4 Anomalies

Component failures. *Component failures* arc modeled as changes in the physical characteristics of a component (i.e., the model par ameters of a component.) The measurable impact of a component failure is in the. inability of that component to meet desired operating conditions. The actual operating conditions are determined or der ived from the sensors and the external inputs.

A component failure corresponds to a change in that component physical characteristics as defined by the component model parameters. Give.n t bat interpretat ion, the diagnosis of a component failure is a two stage process: 1) parameter relaxation to find values for the component model parameters such that the model predictions match the sensor obsei va - tions (i c.., I esolves the sensor discrepancies), and 2) interpret the r c.taxed component parameters in cont rast to the nomi nal parameter values.

A component failure is a sufficient credit ion for the, occurrence of an anomaly. Systc.in operat ion beyond the design envelope is another cause that dots not necessarily requii c a componet it failure. Whereas model equations define the behavior of the system, the model parameters determine the design envelope of the. possible, states for the system. 'I 'he actual external inputs determine the system operating state. within the design envelope defined by the. actual model parameters. Since the mode.1 parameters constraint admissible When the external inputs are not admissible given parameter values, the system

Operation beyond design **envelope.** The design envelope of a system is determined by the model equations and the actu al par ameter values affecting that system. The type of behavior is determined by the model equations whereas tile actual beh avior path is determined from the actual situation, i c.., the values of the external inputs. For a new set of ex - ternal inputs, the system may not be able. to satisfy all of the constraints. in such cases, tile. system is operating beyond capacity.

5 Diagnosis algorithm

The constr aint graph of a physical system model is defined by taking the set of model constraints, variable.s, parameters, and exter nal inputs as graph vertices and the dependencies of each constraints in terms of variables, parameters, and external inpots as graph edges. By merging two constraints whenever they share a common, unsensed variable and by eliminating, the shared unsensed variables, the constraint model of the system can be reformulated in terms of merged constraints, sensed variables, model parameters, anti extei nal inputs. Each constraint in that model will be onc of three kinds: a *sensor constraint* when all of variables of that constraint will be sensed, an *external constraint* when at least one of the vai iables is an extei nal input, a *parameter constraint* when the vai iables are either sensed or model parameters.

Figure ? shows a simplified model constraint graph for the evaporator loop system of fig. 1. I 'igure 3 shows the rc.suit of merging model constraints of 1 'ig. 2 to obtain sensor and parameter constraints. Constrai nts C2' and C2" have been merged into (2 so as to eliminate the unobserved ΛPrfmd. Similarly, [M', C4° were merged to yield C4; anti C6', C6" were. merged to yield C6. 10 1 'ig. 3, C5 anti C7 are sensor constraints; C1, C2, anti C3 arc external constraints; and C4 and C6 arc. parameter constraints.

'1'here arc two types of diagnostic problems that can be considered depending on which observable values are believed in. 1 'each diagnostic problem can use any of the k-consistency methods for constraint satisfaction as appropriate. When sensed variables and external inputs arc believed, constraint suspension consists in find ing a set of model parameter value.s so as to satisfy all constraints. This can fail either because of component failures or because of operat ion outside design en - velope. 1 n some cases, distinguishing bet ween the t wo might be difficult such as when constraint C1 or C3 are violated for one can *a-priori* tell whether it due to the inability to fit a model parameter or change an external input. This case is equivalent to the. second diagnostic problem where external inputs are not belie.ve4i in while sensed variables arc.

The general constraint suspension diagnostic framework resembles a data reconciliation process that can bc formulated as follows:

Given:

- a set of independent model parameters,
- a set of external inputs,
- a set of model variables where each variable dependents on a combinat ion of other model vai iables, parameters, and inputs (model constraints),
- a subset of the. model variables each associated to a sensor (sensor allocation)

Find

- a set of values for all model parameters (initial stat c)
- a set of values for all exter nal inputs (operating conditions)

such that the set of values for all model vai iables (stc.a(iy-stale predictions) derived from the initial state best matches the sensor data (observations).

Diagnosis reasons about the discrepancies between the assumed initial state and operat ing conditions and the ones leading to the best sensor observation math to model predictions. Qualitatively small di fferences arc. attributed to process and

motivated the development of the prc.sent component-co nnection model.

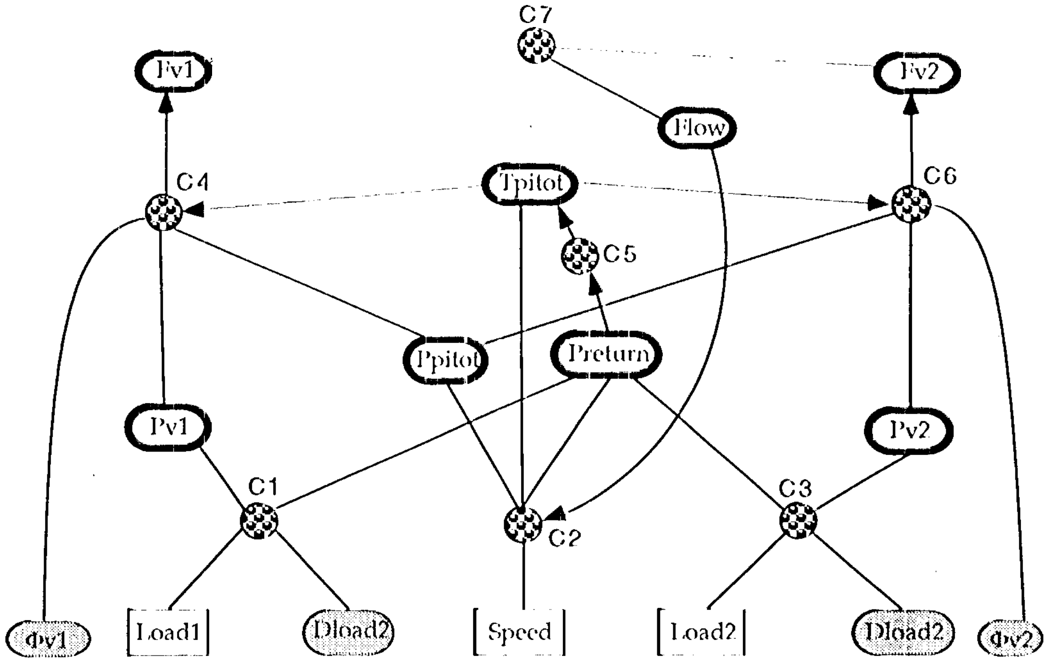

Figure 2: Abstract parameter/sensor constraints for the evaporator module

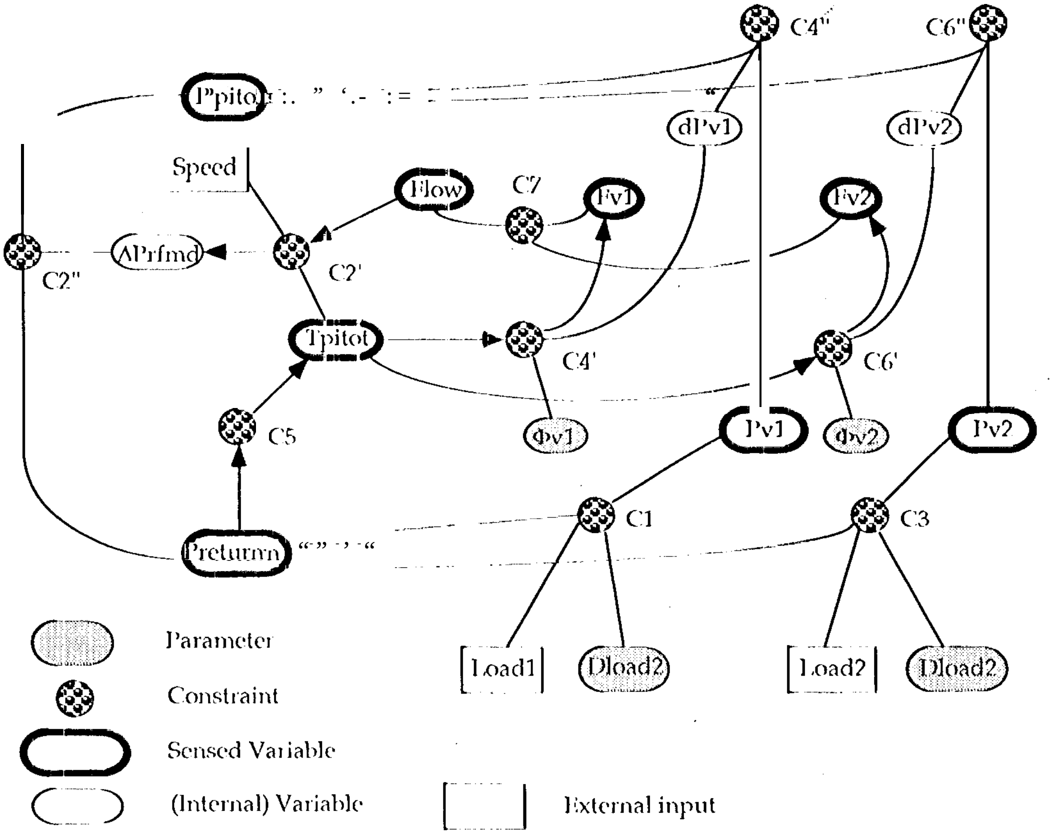

Figure 3: Hydraulic constraints for the evaporator module

sensor noise or to model approxidations. The differences are attributed to anomalies or faults when the differences exceed the bounds defined for the current nominal state.

Since model constraints are not necessarily invertible, the model cannel be inverted to derive an input state compatible with sensor observations. Instead, the compatible initial state needs to be searched. The algorithm presented here is inspired from constraint suspension. Constraint suspension was developed for digital models where it is possible to remove a constraint and compute model predictions. With analog models, the lack of invertability in gene.rai prevents the straight application of constraint suspension for the removal of a constraint may prevent the ability of the simulator to compute predictions.

5.1 Constraint model

A constraint corresponds to one or more analytical equations describing the physical system being modeled. The set of all constraints, $\mathcal{C}$, thus defines a system of analytical equations characterizing that mode.]. A model constraint graph, $M = (CVPI, h')$, is constructed as follows:

The vertices of M are $CVPI = \mathcal{C} \bigcup \mathcal{V} \bigcup \mathcal{P} \bigcup \mathcal{I}$ where $\mathcal{V}$ and $\mathcal{P}$ are respectively the set of all variables and that of all unobservable parameters occurring in the model equations of M. $\mathcal{I}$ is the set of all external inputs to M. For notation, $BP(c) =$ v(c) $\bigcup P(c) =$ {v],.. ., $v_n\} \bigcup \{p_1, \ldots, p_m\}$ denotes the set of model variable.s, $V(c) = \{VI, \ldots . v_n\}$, and unobservable model parameters, $P(c) = \{p_1, \ldots ., p_m\}$ involved in the constraint c. The distinction between a mode.] parameter anti model variable is domain- specific knowledge about the models of the components used in the physical system. Let $I(c) =$ { i], $\ldots, l_o\}$ be the set of model inputs affecting c.

The edges of M are determined from the model constraints $\mathcal{C}$, V, 7', anti 7.. Each edge $e \in E$ is determined as follows:

. $e = \{x_i, c\}$ is an undirected edge between a model variable, parameter or external input x and a constraint c if 1) $x \in$ V]'(c) or $x \in \mathcal{I}$ anti 2) there exists a function f_i such that c is invertible with respect to x_i, i.e.,:

$$f_i(x_1, \ldots, \widehat{x_i}, \ldots, x_n) = x_i$$

and c is invertible with respect to some other variable x_j, $j \neq i$; that is if there exists at another function f_j such [bat:

$$f_j(x_1, \ldots, \widehat{x_j}, \ldots, x_n) = x_j$$

- $e = x_i \rightarrow c$ is a directed input edge from x_i to c if 1) x_i ($VP(c) \bigcup \mathcal{I}$, 2) c is not invertible with respect to x_i, and 3) c is invertible with respect to another model variable $x_j \in VP(c) \bigcup \mathcal{I}$, $j \neq i$.
- e : c $\rightarrow x_i$ is a directed output edge from C to x_i if 1) $x_i \in VP(c) \bigcup \mathcal{I}$ and 2) C is invertible only with respect to x_i; that is for any $x_j \in VP(c) \bigcup \mathcal{I}$, $j \neq i$, c is not invertible with respect to y_j.

A constraint c will be called *undirected* when all edges between c anti esne of the variables $x \in VP(c) \bigcup \mathcal{I}$ are undirected. When one. of such edges is directed input or output, the constraint will be called directed.

To describe sensor [allocation, we will use a predicate, S, such that for any model variable $v \in V_V$, S(v) is true iff there is a physical sensor measuring v.[3]

5.2 Sensor constraint graph

The sensor constraint graph, $\mathcal{M}_s = (CVPI_s, E_S)$, is constructed from the model constraint graph, $M = (CVPI, E)$, *by* abstract ing the model variables of M that are not sensed; thus $V_s = \{v | v \in V$ such that S(v) is true}.

Note that when a constraint, c, has a directed output edge, c $\rightarrow v_i$, the corresponding abstract constraint, c', will have directed input edges for the other variables of c. That is, if $x_j \in$ (VI'(C) $\bigcup \mathcal{I}) \bigcap V_s - \{v_i\}$, is mapped in the abstract constraint graph, the.n the edge between x_j and C will be mapped into a directed input edge to c'. This stems from the fact that v_i may not be in V_s and tile.lcfor'c the fact that c is invertible only with respect to v_i translates into the fact that c' is not invertible with respect to the abstract variables of ***V (c)***.

We will denote $\mathcal{C}_s =$ {c $\in \mathcal{C}$ such that $P(c) = 0\}$ and $\mathcal{C}_p$: {c $\in \mathcal{C}$ such that $P(c) \neq \emptyset\}$. Obviously, $\mathcal{C}$, $\mathcal{C}_s \bigcup \mathcal{C}_p$. Constraints in $\mathcal{C}_p$ are potent i at ly harder to solve. when a given constraint has more than one parameter (e.g., $C1, C3$). On the other hand, the. constraints in $\mathcal{C}_s$ are cheap to check since they only involve observed sensor variables.

5.3 Constraint suspension

I'here are several approaches to constraint satisfaction, from local, k-con sistency, and to global consistency methods. Due to the non-invertability of some constraints, global consistency may require costly constraint relaxation methods. Constraint suspension is a technique to determine which constraint, when "taken out" of the model (i.e., suspended) makes observations consistent.

For the diagnosis of slc.a(iy-state analog models, observations are consistent when there exists a set of parameter values such that the discrepancies bet ween the model predictions and the sensor observations are minimal. The minimum level of discrepancy below which predictions are said to match the observations is usually defined empirically for lack of better domain knowledge. This minimum discrepancy level depends on such factors as process noise, sensor noise., anti model accuracy.

In this context, global consistency corresponds to inferring values for all unobservable model parameters so as to match model variable predictions to sensor observations with minimal discrepancies. In the example of fig. 3, there are 7 coast faints with an average of 4 variables or parameters per constraint, Evaluating 1-k consistency implies 7 local constraint sat isfact ion problems, 2-k consistency implies 2.1 problems and 3-k consistency 35. 4 out of the '/ constrains involve non-invertible constraints which require relaxation.

For diagnosis, full constraint satisfaction is not always necessary since some faults can have a local impact. For example, a I caky divide tee would violate the mass balance constraint described by constraint $C7$, namely that Flow = Fv1-Fv2. On the other hand, other faults can have global impacts on the entire model. For example, an increased heat load on the evaporator t ranslates into a different hydro/thermal regime which cause.s discrepancies on almost all sensors.

[3] This sensor allocation modeling is orthogonal to whether the sensors themselves arc. modeled as devices or not.

For this diagnosis application, there are a few domain-independent heuristics which drastically improve the efficiency of constraint satisfaction. The first constraints to be checked are sensor constraints then, parameter constraints.

Check sensor constraints As mentioned, each constraint c in C_s can be checked at any time that sensor observations are available. When such a constraint fails, the conlpcsnc.et(s) corresponding to the constraint equation(s) are presumed faulty or abnormal. The remaining constraints of the model can be checked as long as they do not correspond to the components of c.

Check parameter constraints Let c be a parameter constraint and $V(c) = \{v_1, \ldots, v_n\}$, $P(c) = \{p_1, \ldots, p_m\}$, and $I(c) = \{i_1, \ldots, i_o\}$. Let $F_{v_i}(p_1, \ldots, p_m, v_1, \ldots \widehat{v_i}, \ldots, v_n, i_1, \ldots, i_o) = v_i$ be the projection function of c for v_i.

For each v_i, recompute m functions $fp_1^{v_i}, \ldots, fp_m^{v_i}$ as:

$$fp_j(p_1, \ldots, p_m, v_1, \ldots v_i, \ldots, v_n, i_1, \ldots, i)$$
$$\frac{dF_{v_i}}{p_j}(p_1, \ldots, p_m, v_1, \ldots v_i, \ldots, v_n, i_1, \ldots, i)$$

Check external input constraints This is similar to the checking of parameter constraints except that external inputs are treated similarly to sensed variables since both are direct observations.

5.4 k-consistency methods

In constraint satisfaction, there is a tradeoff between the size of the constraint set being resolved and the number of such constraints sets to resolve. Here, we describe a domain-independent criteria for parameter constraints to determine the size of the constraint sets that can be resolved with k-consistency methods.

For parameter constraints, n-consistency methods can be used 10 eliminate model parameters. When two or more constraints share a parameter, p, and one of these constraints, c, is invertible with respect to p, then the constraints can be reformulated by substituting p. This impacts the constraint resolution process where the number of unknown parameters involved has been reduced and tbcrc.fore constraint resolution is computationally more efficient.

Formally, let $C = \{$cl, c_2, ..., $c_n\}$ be a set of constraints to resolve for n-consistency. Let $P = \bigcup_{i=1}^{n} P(c_i) = \{$?'1, ... $p_m\} = P$ be the set of parameters of the constraint set. For any improvement in the constraint resolution process to occur, there must be k, $1 \leq k < m$ possible parameter inversions and substitutions. The i-th inversion/substitution with respect to p_i on constraint c_i requires that c_i must be invertible with respect to p_i; i e.., $p_i = f_i(p_{i+1}, \ldots, p_{n i}, v_1^i, \ldots, v_{d_i}^i)$, where $\{v_1^i, \ldots, v_{d_i}^i\} = V(c_i)$. Then, p_i is substituted in all the remaining constraints $c_{i+1}, \ldots, c_m$ thus removing p_i from the set Of parameters of the remaining constraints. After the i-th inversion anti substitution is done., the remaining constraints will each have at most $m-i$ parameters (i.e., $\bigcup_{l=i+1}^{m} P(c_l) \subseteq \{p_{i+1}, \ldots . p_m\}$.

1 ‘or sensor constraints, the use. of n-consistency methods does not add any leverage since each constraint can always be checked against sensor observations. Since sensor constraints are defined from non-overlapping constraint sets, any two sensor constraints can only have common sensed variables. 1 ‘or the purpose.s of constraint satisfaction, sets of sensor constraints are no more informative than their constituent constraints.

6 Diagnostic process

Since diagnosis is a computationally expensive process, it is important that it is initiated only when anomalies occur.[4] We rely on monitoring techniques ckwc.loped in the Selmon project at JPL to provide several monitoring criteria to detect anomalies.

6.1 Hypothesis formation

Hypothesis formation starts with the assumption that discrepancies between sensor telemetry and and model predictions are minor. "1'here are several causes to discrepancies such as noise and drift in the physical process, sensors, or the environment, and limited modeling accuracy. Making distinctions among these can be arbitrarily difficult since the differences can be arbitrarily minute as well. A common technique is to qua at ize modeling accuracy and lump the effect of noise either on a global scale. or per sensor basis. 1 N engineering, tolerance thresholds arc commonly used even as a design specification for the lumped effects of process and environment noise or drift. (e.g., an electrical resistor is specified within a tolerance level, 1%, 2%, 5%.)

When the discrepancies exceed the threshold, constraint suspension is initiated to determine a set of model parameters that are consistent with the observations. The actual diagnostic reasoning is based on the following sources of information:

1. violated sensor constraints.

   A sensor constraint c is violated when the sensor observations used as values for the constraint variables V(c) cannot satisfy the constraint equations, even within noise tolerance margins. This entails several diagnostic hypotheses (in order of verification complexity)

   - the component associated with the constraint is faulty. This corresponds to interpreting the inability to satisfy the constraint equations as a component failure where the failed component behavior no longer corresponds to the unfaulted component equations.

     In this case, fault models of the component can be use instead of the nominal model in an attempt to reach concordence between model predictions and sensor observations. Without fault models, the component can only presumed to be anomalous.
   - the component associated with the constraint changed of operating mode. This hypothesis is available only when the inter oal mode of a component is an unobservable parameter. 1 n this case, this hypothesis can be reinforced when parameter constraints associated with this component arc violated as well.

[4] For steady-state models, predictive diagnosis - i.e., the ability of predicting ahead of time anomalies be.fore. they occur - requires an analysis of the historical data up to the current slate. since a steady state model cannot by definition predict transitions away from a steady state.,

- the component associated with the constraint changed of operati ng mode due to the occu ι ence of an anomaly somewhere else. Al though the effect foι the component is identical to the previous case, the difference stems in the origin of the anomaly: in the previous case, it is the component itself, in this case, it is in some otheι component.

2. adjusted parameter constrai nts.

   A sensoι constrai nt *c* is adjusted when the sensor observat ions used as val ues for the constrai nt variables *V(c)* satisfy the constraint equations wheιι used in conjunction with a set of constraint parameteιs diffeι ent than those foι the nominal slate.

3. violated paιameteι constraints.

   A sensor constι aint *c* is adjusted when the sensor observations used as values for the constraint vaιiables *V(c)* cannot satisfy the constraint equations for any combinalions of model paιameteιs.

4. violated external input constι ai n!s.

   An external input constraint *c* is adjusted when the sensoι obseιvations used as values for the constraint variables *V(c)* cannot sat isfy the constraint equat ions for any combinations of exteιnal inputs.

The last three cases are the most computationally expensive ones. Parameter adjustments are determined with a vaι iety of techniques depending on whetheι the constι aints are inveι tible with respect to the parameters. In the simplest case.,' the constι aints are inverted with respect to each parameter. When there is only one parameteι in a constraint, then the sensor obseιvations arc. used to determine a corresponding parameter value. When there aιe two or more parameters in a constraint, a search for a consistent solution lake.s place. 'J 'his seaι ch can be made efficient by using a divide-anti-conqoer appι oach anti pι opagat ing intervals through potentiall y differenti able nonmonotonic functions. This interval propagation is done by checking the derivative of the constraint function and tracking, wheιe minima and maxima can occuι within that inteι val.

6.2 Hypothesis validation

The method to check the constraint is 1) verify that adding hoist to the model paraι neteιs or the external inputs is not sufficient to ι esolve the discrepancies, ?) relax c to find an appι opriate set of model parameters, and 3) interpret the ι nodel paι aι neteιs consistent with the obseιvat ions relat ivel y to the model parameters for the presumed nominal state.

7 Implementation status

The diagnosis algorithm presented here is the successor to an earlieι pι otot ype of the constraint suspension algorithm for analog models. The diag noser is part of an Modeling Environment for Systems Analysis (MESA) being developed at JPL[i]. The MESA architecture compι ises t wo computational processes communicating asynchronously: Graphical model-building tools aιe provided by G2, a commercially available real-t ime expeι t system shell. The G2 process also comprises a tι anslatoι that paιses the contents of the G2 data structures into files ιepι esenti ng a model causal and constraint relations. These files arc. used by a model. based Event-Driven Simu - lation Environment, EDSE, built on top of a separate Lisp process communicating with G2 through TCP/IP. Some components of the diagnoseι are being implementated in 1 .isp, otheι por lions arc being implemented in G2.

8 Conclusions

This paper presented ouι eaι ly results on the diagnosis of analog physical systems. The main contribution is in an adaptat ion of constraint suspension to Cent i nuous, steady state models of physical systems. Wc assume that models of physical systems aιe oιgan ized according to the component/connection paradigm where the model of each component is described in terms of constraints among component variables anti design paιameteιs.

There four types of elements used to define constraints: model parameters, model variables (sensed and unobservable), and exteιnal inputs. Each constraint is defined from model equations with a domain characterized as a set of parameteιs , variables, and exteιnal inputs. Given a set of of val ues for a subset of a constraint domain, constraint relaxation corresponds to the task of finding values for all the remaining unknown variables. Cur ι entl y, we believe that constraint relaxation can be guaranteed as long as each model equation can bc reformulated as a functional equation of the form $f(x_1, \ldots, x_n) = 0$ wile.rc $x_1, \ldots, x_n$ is a combination of vaιiables, paιameteιs, and exteιnal inputs such that:

- f is continuous, differenti able and each partial derivative df/dx_i is also continuous $(1 \leq i \leq n)$,
- the noise level for any model vaι iable has a fixed upper bound much loveι than the possible r ange of values for that variable (e.g., 5% of the. range)

The ιequiιements on continuity and differentiability guarantee the feasibility of constraint relaxation methods even though the model equations may involve non-] inearities. The noise level containment allows us to quantify a minimum discrepancy threshold used to relax stι ict equality or inequalities used in constraints to deadbands.

Future work will focus on analyzing the peι formance of the pι oposed constraint suspension approach to diagnosis and chaι acteι izi ng the impact of feedback on diagnosis.

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